A Survey of Social Emotion Prediction Methods

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Abstract: Emotions are an important factor that affects our communication. Considerable research has been done to detect and classify emotion in text. However, most deal with emotion from the writer's perspective. Social emotion is the emotion of the reader when exposed to the text. With the increased use of social media, many works are performed for social emotion prediction. In this paper, we attempt to provide a survey of social emotion prediction methods. To the best of our knowledge, this is the first work to survey the literature of social emotion, review methods, and used techniques, compare the methods, and highlight their limitations.

1 INTRODUCTION

Emotion analysis in Natural Language Processing is an active research area that seeks to automatically detect emotion expressions in text, typically grounding on pre-defined, psychology based emotion models (Alswaidan and Menai, 2020; Strapparava and Mihalcea, 2008). It extends research on sentiment analysis, by providing an understanding of the text deeper than the shallow classification in positive, negative, and neutral valence (Yadollahi et al., 2017).

The vast majority of work so far has focussed on identifying the emotions of the *writer* of the text, that is the expressed emotion as an indication of the writer's feelings or state of mind, often driven by applications in market analysis and analysis of consumer reviews. However, more recently a trend has emerged which focusses on studying the emotion that the text provokes in the *readers*, with many applications in social sciences and again marketing, for instance tracking generated sympathetic responses to potentially emotional events, or predicting the emotional effect of advertisements. Research has focussed on the distinction among viewpoints, for instance those of the reader's as opposed to the writer's (Lin et al., 2008), or the perspective of the text itself as a third point of view (Buechel and Hahn, 2017).

The term *Social emotion* has recently emerged to indicate the aggregation of readers' emotional responses, as collected by mining the social web for comments, blogging, reactions etc. (Bao et al., 2012; Rao et al., 2016), and represented either as a distribution over emotions that quantify readers' rankings, or as a single dominant emotion (Lin and Chen, 2008).

Social emotion prediction is the task of identifying the social emotion that is likely to be provoked by a text, where the text is usually objective, or at least not emotionally loaded (Li et al., 2017a). The task is challenging as readers' emotions are likely to be affected by their background and personal experiences, which are unknown and not necessarily declared. As an emergent research topic, the field is also lacking from the benefit of numerous labelled datasets, which are crucial for good quality supervised learning approaches (Alswaidan and Menai, 2020). This is especially true for English[1], while there are several datasets for Chinese, thanks to news portals features enabling readers to use various emotion labels to express their feelings.

In this paper we provide a survey of social emotion prediction methods and systems, by classifying surveyed work into three main categories on the basis of the main strategy used for prediction.

2 SOCIAL EMOTION PREDICTION METHODS

Existing social emotion prediction works can be classified into three categories depending on whether they

[1] A notable exception is EMOBANK (Buechel and Hahn, 2017) a bi-perspectival large-scale 10K English dataset annotated with writer's as well as reader's emotion.

are based on words, topics, or deep learning.

Word-based methods are based on the assumption that all words, even neutral ones, can be associated with a likelihood to provoke emotions (Strapparava and Mihalcea, 2007). These can be effective, but performance is affected negatively by sentiment ambiguity of words in different contexts and noisy words.

Topic-based methods link emotions to broader topics/events rather than single terms (Bao et al., 2009), and use the machinery of topic modelling (Blei and McAuliffe, 2007) to introduce an intermediate emotion layer. The main criticism to these methods is that they do not consider the order of words and cannot encode the sequence information in text.

More recent methods are based on techniques coming from deep learning, such as deep neural networks and word-embeddings, used to overcome, for instance, the problem of sparsity associated with topic based methods (Li et al., 2017b).

In remaining of this section, we will discuss social emotion prediction methods in each of these three categories, looking at the methods, the techniques used, the language, and the type of prediction, whether a single, predominant emotion label, an array of multiple emotion labels representing the readers' emotion distribution, or as a ranking problem. A summary of all surveyed works against these features is provided in Table 1.

2.1 Word-based Methods

Social emotion prediction works are considered to have been first appeared at the 2007 *SemEval* workshop, in its Task 14 on *Affective Text* (Strapparava and Mihalcea, 2007). All participating systems to SemEval-2007 Task 14 adopted a word-based method for classifying social emotion into the six basic emotions identified in (Ekman, 1992), and they were all based on English, as such was the corpus provided for the task. SWAT (Katz et al., 2007), one of the top-performing systems, used a bag-of-words (BOW) model trained to label news headlines with emotions, by expanding on synonyms and antonyms using Roget's Thesaurus to improve the prediction accuracy. The system scored each word and considered the average score for the headline. The authors used the SemEval-2007 Affective Text corpus for training and evaluation, in addition to annotating 1000 headlines for training. UPAR7 (Chaumartin, 2007), developed a rule-based classifier that depends on syntactic parsing and utilises resources from WordNet, SentiWordNet, and WordNet-Affect. The system was evaluated on SemEval-2007 Affective Text corpus and achieved comparable results to SWAT. The authors suggested the exploration of statistical models for future work to improve the classification recall. UA-ZBSA (Kozareva et al., 2007) adopted a slightly different approach based on the principle that adjectives with similar polarity appear together (Hatzivassiloglou and McKeown, 1997; Turney, 2002). The system utilises web search engines (MyWay, AllWeb, and Yahoo!) to measure the *Mutual Information score* between the emotion and the BOW of headlines.

Another notable early work collected 17,743 news articles from Yahoo!China and the reactions expressed by its users for training a supervised system (Lin et al., 2007; Lin et al., 2008), exploiting a functionality in Yahoo!China that allows users to express their feelings after reading news articles by using one of more reactions among: happy, angry, sad, surprised, heartwarming, awesome, bored, and useful. The authors extracted features like unigrams, bigrams, metadata and also used a lexicon to obtain emotion categories of words. Then, a Support Vector Machine (SVM) was trained with these features using 12,079 articles. The model was tested with 5,664 articles. Their results show an accuracy of 87.9% in predicting the predominant emotion in each article. In another work, the authors tackled the different problem of ranking the possible readers' emotions regarding a certain text (Lin and Chen, 2008). They used pairwise loss minimization and regression using Support Vector Regression (SVR) to produce a list of ranked emotions that related to the text. The authors stated a high decrease of accuracy, which shows the difficulty of the ranking task for emotion classes.

Parallel to this, work in Japan used distant supervision to obtain a dataset for emotion-provoking events (Tokuhisa et al., 2008). The authors searched the web for lexical patterns that represent expressions about emotional events, such as "*I was disappointed that*" and linked the emotion of disappointment to the rest of the sentence, for example "*it suddenly started raining*". This resulted in a corpus of 1.3 million events in Japanese with their related emotions, which was used to build a two-step k-Nearest Neighbour (kNN) classifier for sentiment polarity and emotion.

Other work developed a multi-label emotion classifier using RAkEL, an ensemble model for multi-label classification (Bhowmick et al., 2010). The classifier was trained for emotion classification on news sentences collected from news archives. The emotion categories covered are disgust, fear, happiness and sadness. The system used unigrams as a feature, in addition to subject polarity, verb and object of the sentences, and semantic frame from FrameNet to explore semantically related words. The Emotion-Term model (Bao et al., 2009) was proposed to map

	METHOD NAME and/or SOURCE	PREDICTION	DESCRIPTION	LANGUAGE
Word based	SWAT (Katz et al., 2007)	Multi-label	BOW model + word expansion	English
	UPAR7 (Chaumartin, 2007)	Multi-label	Rule-based	English
	UA-ZBSA (Kozareva et al., 2007)	Multi-label	Knowledge-based + Statistics (PMI)	English
	(Lin et al., 2007; Lin et al., 2008)	Single label	Support Vector Machine classifier	Chinese
	(Lin and Chen, 2008)	Ranked list	Pairwise loss minimization and regression	Chinese
	(Tokuhisa et al., 2008)	Single label	k-Nearest Neighbors classifier	Japanese
	(Bhowmick et al., 2009)	Multi-label	Ensemble classifier	Chinese
	Emotion-Term model (Bao et al., 2009)	Single label	Naive Bayes classifier	Chinese
	(Tang and Chen, 2011)	Single label	Support Vector Machine classifier + non-linguistic features	Chinese
	(Wang et al., 2011)	Ranked list	Rank-LR	Chinese
	(Ye et al., 2012)	Multi-label	Ensemble classifier	Chinese
	(Liu et al., 2013)	Single label	Maximum entropy classifier	Chinese
	(Lei et al., 2014)	Single label	Document selection, Part-of-speech tagging, Emotion lexicon	Chinese
	(Yao et al., 2014)	Multi-label	RAkEL + Knowledge-level resources to enlarge the features	Chinese
	(Vu et al., 2014)	Multi-label	Pattern expansion + Clustering	English
	(Li et al., 2016a)	Single label	Conditional Random Field + Support Vector Machine	English
	Textual Relevance (Ramya et al., 2019; Ramya et al., 2020)	Single label	Word frequency and nearest neighbour analysis	English
	Hidden Topic - Emotion Transition model (Tang et al., 2019)	Multi-label	Emotions-topic transition w. Markov chain + linguistic features.	Chinese
Topic based	Emotion-Topic model (Bao et al., 2009; Bao et al., 2012)	Multi-label	Additional emotion layer on LDA	Chinese
	(Xu et al., 2013a)	Multi-label	LDA + multi-label k-Nearest Neighbors classifier	Chinese
	(Xu et al., 2013b)	Multi-label	PLDA + multi-label classifiers	Chinese
	MSTM (Rao et al., 2014a)	Multi-label	Extension of supervised topic model (Blei & McAuliffe, 2009)	Chinese
	SLTM (Rao et al., 2014a)	Multi-label	Generates topics directly from social emotions	Chinese
	ATM (Rao et al., 2014b)	Multi-label	Jointly link topic to emotions and words	Chinese
	(Quan et al., 2015)	Single label	Latent Discriminative Models	Chinese
	ML-sETM (Zhang et al., 2015)	Multi-label	Supervised topic model	Chinese
	WME and TME (Rao et al., 2016)	Multi-label	Topic-model + Maximum Entropy	English
	CSTM (Rao, 2015)	Multi-label	Adaptive social emotion detection	Chinese
	WMCM (Li et al., 2016b)	Multi-label	Emotion concentration w. Topic model to identify word senses	Chinese
	UAM (Liang et al., 2018)	Multi-label	Supervised Topic Model + word-emotion dictionary	English + Chinese
Deep Learning	(Li et al., 2017a)	Single label	Semantic analysis using word- embeddings	Chinese
	(Li et al., 2017b)	Multi-label	Semantically rich hybrid neural networks	English + Chinese
	(Krebs. et al., 2018)	Multi-label	Ensemble model w. of neural network + lexicon emotion miner	English
	(Gambino and Calvo, 2018; Gambino and Calvo, 2019)	Multi-label	MEKA + BOW + Doc2Vec	Spanish
	(Wang et al., 2019)	Multi-label	Syntactic and topical features in deep learning model	English + Chinese
	(Guan et al., 2019)	Multi-label	Hierarchical LSTM based model w. attention mechanism	Chinese
	TESAN (Wang and Wang, 2020)	Multi-label	Unified deep learning model from semantic + topical features	English + Chinese

Table 1: A Summary of Social Emotion Prediction Methods

terms with emotion label using a Naive Bayes classifier. Another interesting work studied the emotion generation on the Plurk microblogging platform from both reader and writer perspectives (Tang and Chen, 2011). Plurk provides both bloggers and repliers the ability to tag their post or comments with an emotion. The work used textual features in addition to non-linguistic features for the model, i.e.: social relation, user behaviour, and relevance degree. The findings were that adding non-linguistic features improved the model performance, and the best accuracy was achieved for textual features with social and behavioural features.

List-LR (Wang et al., 2011) is a method for social emotion ranking, which, unlike previous approaches, such as learning pairwise preference (Pair-LR), used listwise preference, which minimises the listwise loss to rank emotion labels. The method was evaluated on a dataset of 3000 news articles collected from the Chinese news website *Sohu* with encouraging results. Another RAkEL classifier for multi-label reader's emotion prediction in (Ye et al., 2012) performed an evaluation on a corpus from *Sina* news, with the best performance found with Chi-square and document frequency as features.

Plurk was also used in (Tang and Chen, 2012) to investigate the linguistic factors that affect emotion transition between poster and repliers, using the platform log relative frequency ratio. Although the system adopted sentiment polarity (positive, negative and neutral) in the analysis, the dataset was built by categorising 35 emoticons based on their name and popular usage. The extracted sentiment words were used to build an SVM classifier for emotion transition.

Yahoo!Kimo news was used in (Liu et al., 2013) as a dataset for modelling news reader's emotion and comment on writer's emotion. The dataset contains news articles labeled with eight different emotions: happy, sad, angry, meaningless, boring, heartwarming, worried, and useful, though useful and meaningless are not considered as emotions, and were discarded in a separate experiment. Only articles with dominant emotions were selected, and that emotion was considered as the reader's emotion. A semi-supervised model was used to exploit unlabelled data and improve accuracy. Maximum entropy (logistic regression) was adopted as a classifier with unigrams of each article and comment as features.

Another popular microblogging service in China, *Weibo*, was used in (Yang et al., 2013) to predict the social emotions based on user's interest in text and images, in addition to their social influence. The work evaluated the method on data crawled from Weibo, and adopted sentiment polarity (positive and negative) rather than fine-grained emotions. Findings were that user interests and social influence affect user emotions in different ways, and they both improved the prediction performance significantly.

Authors in (Yao et al., 2014) tackled an important issue in the classification of news headline, that is data sparseness: headlines are short pieces of text and therefore insufficient for training a model, or working on the lexicon. The model used HowNet (Dong and Dong, 2003) an online common-sense knowledge base to expand the features, was evaluated on Sina news, with performance comparable to BOW-based approaches using both headlines and contents, which is promising for other short text analysis, e.g. tweets.

More recent work include complex architectures and experimentation, e.g. a system in (Lei et al., 2014) consisting of three modules: document selection, POS tagging, and social lexicon generation, which was evaluated for Chinese and compared results from SemEval-2007. Or, work in (Vu et al., 2014), an extension of (Tokuhisa et al., 2008) meant to overcome its lack of measurement of the quality of events, and of the aggregation of similar events. The authors built a dictionary of emotion-provoking events using both manual and automatic methods: they categorised and ranked a list of events collected by asking 30 participants to describe emotion-provoking events, and enlarged the list automatically from the web using the pattern of (Tokuhisa et al., 2008), with results showing an increase in precision and recall. In a similar experiment (Li et al., 2016a), in order to establish whether specific emotional words are more important for classification of news than other words, crowdsourcing was used to annotate a news corpus, then a Conditional Random Field method extracted emotional words to be used as features in the emotion classifier. The classifier was also evaluated on Semeval-2007 AffectiveText dataset, with a comparable performance to BOW approaches, and improving on other lexicon features. A further increase in performance was achieved by combining this method with BOW.

Finally, it is worth mentioning word-based methods working at document level. An approach based on Text Relevance (Ramya et al., 2019; Ramya et al., 2020) categorised documents into emotion classes using word frequency. The evaluation was conducted on a translated corpus of news articles from Chinese to English, and improved on the similar approach in (Li et al., 2017a). An approach of emotion detection in sentence-level as well as document-level was used in (Tang et al., 2019) working on an assumption that all words in the same sentence share the same emotion and topic, and modelling emotion and topic transition between sentences as a Markov chain. The experiment performed on two datasets showed that the method outperforms state-of-the-art methods on both sentence-level classification and document-level classification.

2.2 Topic-based Methods

The first topic-based emotion prediction method (Bao et al., 2009; Bao et al., 2012) started from the principle that emotion in text is more correlated to the topic than the terms. The model was built upon Latent Dirichlet Allocation (LDA) (Blei et al., 2003) a popular topic modelling technique used in information retrieval, and modifies LDA to add a layer that considers the emotion. The model improved the prediction of social emotion significantly compared to the emotion-term model.

Expanding on this, work in (Xu et al., 2013a) used topic modelling as a dimension reduction method rather than BOW, in addition to multi-label kNN, for a multi-label emotion classification. To implement topic modelling, a weighted LDA was used, which expanded LDA to discover the semantic association between topics and emotions. The approach was evaluated on a dataset from *Sina* containing news labelled with readers emotions. In another work, (Xu et al., 2013b) authors used the output of a Partitioned LDA model as a feature for the multi-label classifier to predict the reader's emotion, again on a corpus from Sina news for evaluation, and found that the system performs better than BOW, LDA and Weighted LDA.

Multi-label Supervised Topic Model (MSTM) and Sentiment Latent Topic Model (SLTM) (Rao et al., 2014a) are two emotion-topic models for social emotion prediction which also introduced an emotion layer to LDA. They were evaluated on 4570 news articles collected again from Sina news, resulting more accurate and stabler than the common emotion-term model. The Affective Topic Model (ATM) by the same authors (Rao et al., 2014b) implemented a multi-label model for detecting social emotion toward certain topics.

Work in (Bao et al., 2009) also introduced an intermediate layer to the topic model, which enabled the extraction of different meanings for the same word. The model was able to distinguish between topics associated with one emotion, and merged topics linked to several emotions. The evaluation was performed on the same dataset from Sina news, and the model significantly outperformed the multi-label supervised topic model, the emotion-topic model, SWAT, and the emotion-term model, and achieved comparable accuracy to the sentiment latent topic model. The model effectively discovered meaningful topics that were related to emotion, and their words can be used for emotion-based information retrieval.

ML-sTEM (Zhang et al., 2015) is a multi-label supervised emotion-topic model which learns through observing the associations of emotion labels linked to the documents, and then uses a modified LDA with an additional emotion layer to produce the emotion-topic output. The evaluation was performed on a dataset from Sina news collecting, for each of the eight emotions that the platform allows readers to use for labelling, the most-viewed news. The authors reckon this is the first multi-label emotion tagging model for news document from the reader's perspective; however, the real novelty of this work is the way that it used a supervised topic model based on LDA.

Work in (Quan et al., 2015) proposed a latent discriminative model by introducing intermediate hidden variables, on the assumption that social emotions are dependent on each other: for example, it is likely for people who are angry to also be sad. A similar principle was used in (Li et al., 2016b) to tackle the problem of unstable performance of previous models, due to noisy training documents, with a multi-label classification model (WMCM) based on 'emotion concentration', which exploits the topic models to identify word emotional meanings in different documents. The model was evaluated on two datasets, SemEval-2007 news headlines and Sina news, and the results showed the effectiveness of the model over the baselines of many systems we covered in the previous sections, such as SWAT, ET, ETM, MSTM and SLTM.

The Context Sentiment Topic Model (CSTM) (Rao et al., 2016) differentiated between context-dependent and context-independent topics. The model provided an adaptive classification by considering the context during the topic modelling stage. In the same work, the authors proposed TME, a topic-level maximum entropy model for social emotion prediction, which combines output from unsupervised topic model with a Maximum Entropy classifier to mitigate the problem of data spareness when learning from short-text. The model was evaluated on a collection of short documents obtained from several sources and manually labeled with reader's emotion. The experiments showed that the model successfully addresses the problem of overfitting on sparse words.

Finally, the Universal Affective Model (UAM) (Liang et al., 2018) classifies short-text in social media into fine-grained social emotions. The model adopts a combination of a supervised topic model with a word-emotion dictionary to solve the problem of data sparsity when dealing with short-text. The model consists of two sub-models: topic-level and term-level. The evaluation was performed on real-world datasets and validated the effectiveness and the improved accuracy that the model achieved.

2.3 Deep Learning-based Methods

The first work that used a deep learning model for social emotion prediction was probably the one described in (Li et al., 2017b), which integrated semantic knowledge with a hybrid neural network (HNN) to produce a semantically rich and effective model. Unsupervised learning models, i.e., Bi-Term Topic Model (BTM), Replicated Softmax Machine (RSM), and Word2vec, were used to extract semantic features in order to use them in the proposed HNN model. Then, the model was trained on a labeled dataset to predict the reader's emotion. The evaluation was performed on three datasets, SemEval-2007, Sina news, and ISEAR (Scherer and Wallbott, 1994) (the International Survey on Emotion Antecedents and Reactions). It was found that the proposed model outperformed state-of-the-art models for social emotion prediction, and it was suggested that semantically rich models better predict different emotion contexts and improve the performance of the predictive model.

The approach in (Li et al., 2017a) used a social opinion model that measures similarity among news documents. A social opinion network was built based on the Wikipedia pre-trained word-embedding. The network consisted of Word2vec vectors where nodes represented the social opinions, and the edges represent their relationships. The semantic similarity was calculated by the distance between nodes and neighbour analysis was used for the prediction. As a result, a strong correlation was found between the news structure and the emotion associated. The model showed a more stable and accurate performance than most of the other models.

Twitter was used in (Gambino and Calvo, 2018; Gambino and Calvo, 2019), a work which investigated the social emotion for Twitter news articles using annotated headlines and replies from popular Spanish news publishers. A multi-target classification model was developed for emotion distribution and their intensity, which assumed that the reader can express more than one emotion for the same article. Different features were used with the model, such as BOW and word embeddings using Doc2Vec. Also, the implementation was performed using MEKA, which is an extension for the WEKA tool that provides methods for the multi-target classification. The classification results were promising in spite of the bias toward few emotions due to the highly imbalanced training data of the emotion distribution.

Facebook was instead used in (Krebs. et al., 2018) where a dataset was built of Facebook posts with their reaction distributions, which was used to train an ensemble model for the prediction of the then five Facebook reactions. The model combined a neural network trained on GloVe vectors, with an emotion miner that uses EmoLex for both posts and comments, also analysing the effect of pre-processing on the performance. It was found that combining baseline models of emotion analysis can improve the performance.

A hierarchical Long Short-Term Memory (LSTM)-based model was proposed in (Guan et al., 2019) with attention mechanism for social emotion prediction, as word-level models suffer from the sentiment ambiguity and noisy words problems. Also, the topic-level approaches are not able to encode the order of words and sentences. The proposed method attempts to capture the semantic of long-text by employing the word-embedding on three different levels: word, sentence, and document. Also, the attention mechanism enables to build an emotion lexicon that could be used in the future. Based on the evaluation conducted on crawled datasets from Sina news, the proposed model achieved better performance than all baselines of word-level and topic-level.

The model in (Wang et al., 2019) considered the semantic and topical information and integrated syntactic features in sentences with topical information in each document to generate a document representation. In the first step, a Deep Ensemble Learning Model (DERN) is used to encode syntactic sentences into vectors, then a Gated Recurrent Unit (GRU) converts those vectors into a document vector. Secondly, an multilayer perceptron (MLP) is used to convert the output of LDA into a topic vector. Finally, a gate layer generates the final document representation from both inputs. Experiments on two datasets from Sina news and ISEAR showed that the proposed model outperforms the state-of-the-art models in terms of Micro F1 score and Average Precision.

A similar model was proposed in another work by the same authors, TESAN, (Wang and Wang, 2020) which also utilises semantic and topical features. TESAN jointly learns features in a unified deep learning structure. The model consists of a neural topic model for topic modelling, a topic-enhanced self-attention mechanism to generate the document vector from the semantic and topical features, and a fusion gate to integrate both inputs and generate the final document representation. TESAN was evaluated again on Sina news and ISEAR, in addition to SemEval-2014 dataset for news headlines. The experiments showed that TESAN significantly improved the state-of-the-art results. Also, the model was efficient and able to generate high-quality topics.

3 DISCUSSION

The survey of social emotion prediction methods clearly show a chronological order of phases of the research, with early works focussing on word-based methods, then moving to topic-based methods, and, recently, a majority of works using the deep learning-based methods. This indicates both a shift in technology and a change in the availability and structure of datasets, with an ever increasing range of possibility for readers to self identify the emotions that they feel while reading directly at the time of reading. Not surprisingly, the type of prediction has also changed, with early systems focussing on searching the dominant emotion associated with a piece of text, up until the possibilities to provide multi-labels and ranked list of labels. Therefore, whilst early word-based models had to rely heavily and almost exclusively on established lexicon such as EmoLex and WordNet, and use word frequency and linguistic features only, topic-based systems can work on intermediate emotion layers such as LDA, and deep learning-based methods benefit from the semantically rich representation that word-embeddings provide. Also, neural network architectures such as CNN, LSTM, and GRU, in addition to the attention mechanism.

In terms of dataset availability and their impact on the natural language used by these methods, clearly the relatively recent practice by China based news portals to allow users to self report a wider range of emotions (e.g. curiosity, amusement, surprise) rather than the limited set of reactions used in Western social media, has given a tremendous push to research in China, and highlighted the need for more datasets on other languages.

One aspect which is perhaps still missing is a greater attention to the context in which the piece of text and the reactions to it are placed, for instance, which social media page features the news, whether the news is shared by specific users or pages or groups, or even a more comparative study of how different platforms, as well as different set of users social media connections, make a difference.

4 CONCLUSIONS

In this survey paper, we reviewed the available methods for social emotion prediction and presented them in chronological order according to three categories: word-based, topic-based, and deep learning-based. Also, we discussed the techniques used in these methods and the different type of predictions. While social emotion prediction is a challenging task, progress in prediction performance is promising, but there is a pressing need for reliable labeled datasets for social emotion in order to train supervised models.

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